# Deep Vision Project: Artist identification and generating new paintings using DC-GAN

**Mitodru Niyogi** and **Antonio Ruiz**

Faculty of Mathematics and Computer Science, Heidelberg University, Heidelberg

## INTRODUCTION AND PROBLEM DEFINITION

**Artist identification** of fine art paintings is an important requirement for cataloguing art, especially as arts are being increasingly digitized. We trained Convolutional Neural Networks (CNNs) with the goal of identifying the artist of a painting as accurately possible. Moreover, we also tried to generate **novel paintings** by using deep learning models applied to a set of specific paintings.
Basically our aim is to solve the following problems:
**Problem 1: Given a painting, identify the artist who created the painting?**
**Problem 2: Generate new paintings based on genre, style or artist.**

## DATASET

It is composed by roughly 100,000 paintworks (png images) created by about 2300 distinct artist from different painting style and genre. The data is split into 77% for training and 23% for testing.
The main source of the dataset is wikiart.org, it can be downloaded from: https://www.kaggle.com/c/painter-by-numbers/data

## PROPOSED ARCHITECTURE

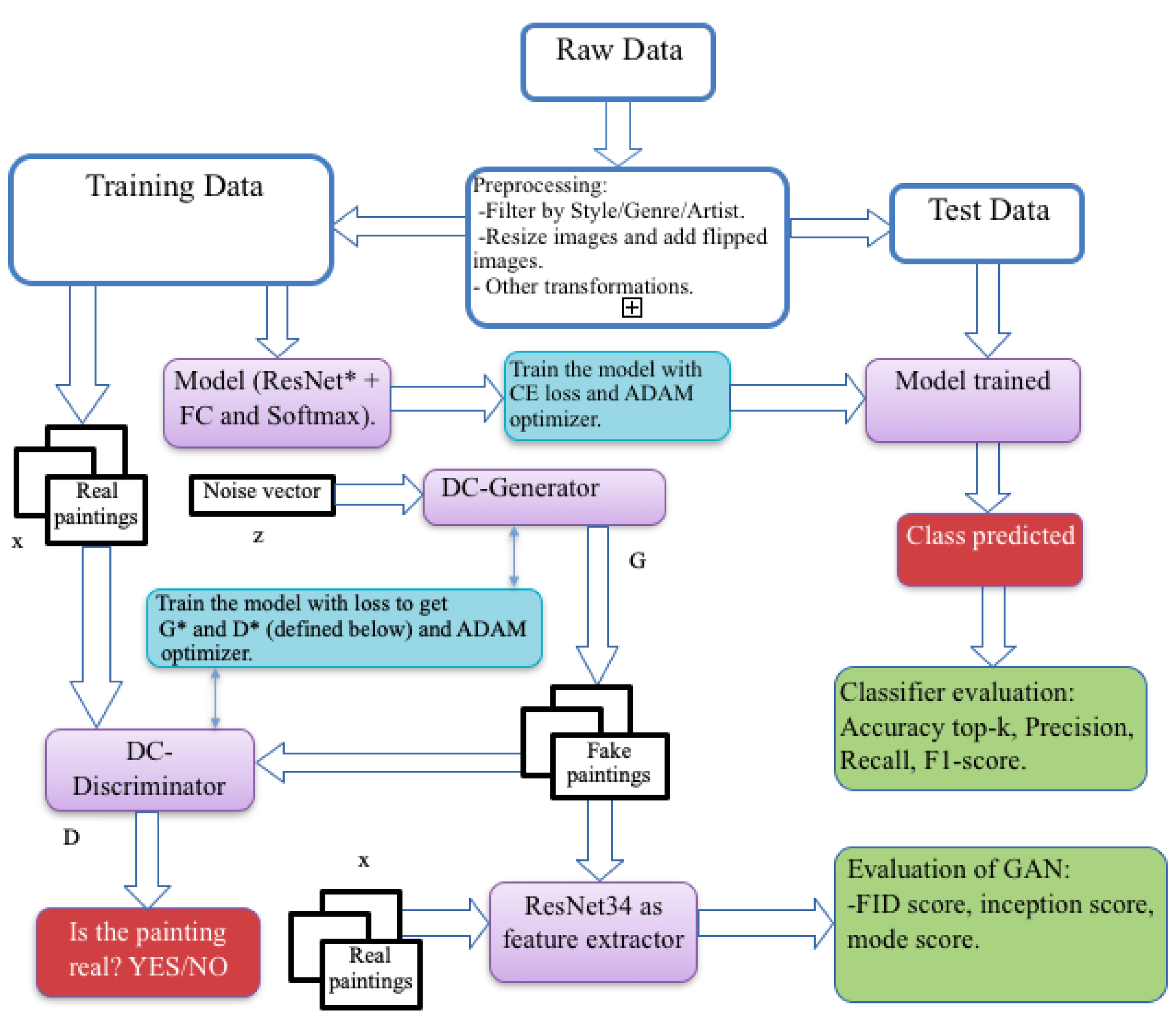


Fig. 1: Proposed architecture

## BACKGROUND

**Convolutional Neural Network:** Neural networks that employ a mathematical operation called convolution. They are the building blocks of the most of the algorithms used in computer vision.
**Generative Adversarial Networks:** It's a machine learning system where two neural networks (generator and discriminator) contest with each other in a game (in the sense of game theory) of generating and discriminating the generated data.
**Evaluation of GANs: [3]**
**FID Score:** FID models $\phi(\mathbb{P}_r)$ and $\phi(\mathbb{P}_g)$ are Gaussian random variables with empirical means $\mu_r, \mu_g$ and empirical covariance $C_r, C_g$, and computes
$FID(\mathbb{P}_r, \mathbb{P}_g) = \| \mu_r - \mu_g \| + \mathrm{Tr}(C_r + C_g - 2(C_r C_g)^{\frac{1}{2}})$
**Inception score** It calculates the average KL divergence between conditional and marginal class distribution over generated data.

$$IS(\mathbb{P}_g) = e^{\mathbb{E}_{x\sim\mathbb{P}_g}[KL(\rho_M(y|x))||\rho_M(y)]}$$

Where M is the image classfication model pretrained on ImageNet dataset, $\rho_M(y \mid x)$ denotes the label distribution of x predicted by M, and $\int_x \rho_M(y \mid x) d\mathbb{P}_g$ is the marginal of $\rho_M(y \mid x)$ over the probability measure $\mathbb{P}_g$.
**Loss used to train the DC-GAN:**

$$\hat{D} = \underset{D}{\operatorname{argmax}}\, \mathbb{E}_{x\sim\mathbb{P}^*}[log(D(x))] + \mathbb{E}_{z\sim\mathbb{P}}[log(1 - D(G(z)))]$$

$$\hat{G} = \underset{G}{\operatorname{argmax}}\, \mathbb{E}_{z\sim\mathbb{P}}[log(D(G(z)))]$$

## MODELS & METHODOLOGY

**Task 1: Artist identification** The data was preprocessed by filtering just the images present in both training and test set, some thresholds based on the number of paintings per artist were utilized to test the model, the final threshold used was 300. Several models were used to tackle the problem of identification of the artist. The backbones used were ResNet18 and ResNet34 [1].

**Task 2: Painting Generation** The dataset has been filtered by genre, style, and also by artist. The filtered dataset has been trained using DC-GAN architeture to generate novel paintings based on different genres such as potraits, landscapes, etc. We also generated novel paintings just by training on the entire dataset which is a mix of different styles, genres, and artists. Architecture used: Deep Convolution Generative Adversarial Networks [2].

## QUALITATIVE RESULTS

In order to show the qualitative results we present the following images, by comparing the real data VS the fake data.

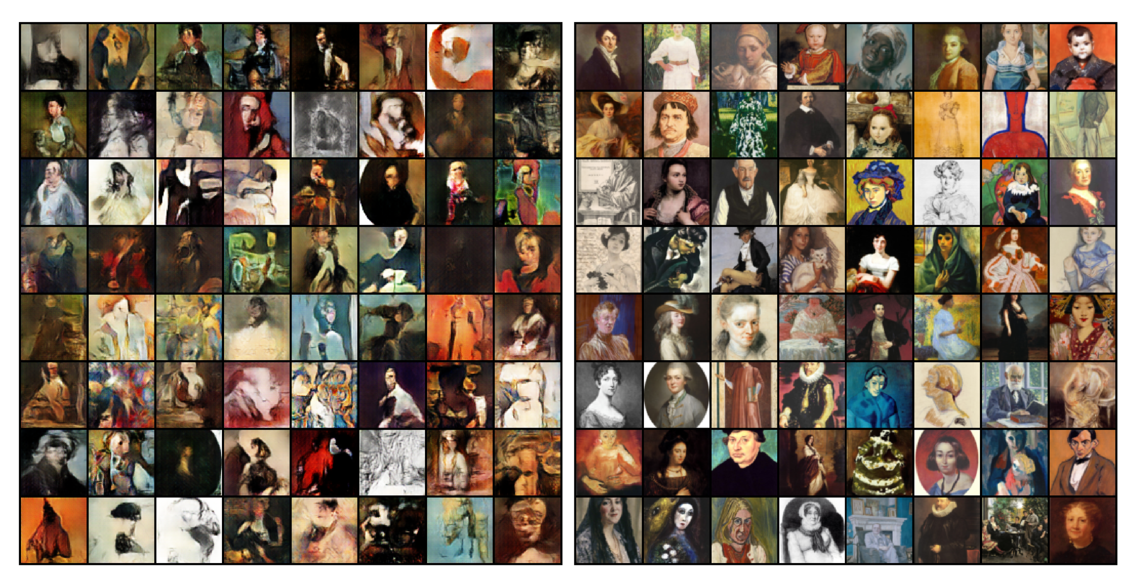

Fig. 2: Fake portraits VS Real portraits

Fig. 3: Fake landscapes VS Real landscapes

Fig. 4: Fake data VS Real Data

## EVALUATION

**Task 1:** To evaluate how well our classifier performs we take the following measurements presented in the following table:

| Measurement | Model with backbone Resnet18 | Model with backbone Resnet34 |
|---|---|---|
| Test accuracy topk (1,3,5) | (0.85, 0.96, 0.98) | (0.81, 0.95, 0.98) |
| Train accuracy topk (1,3,5) | (0.84, 0.95, 0.97) | (0.80, 0.94, 0.97) |
| Precision | 0.8594 | 0.8275 |
| Recall | 0.8509 | 0.8125 |
| F1 score | 0.8508 | 0.8121 |

**Task 2: Evaluation of GAN performance**

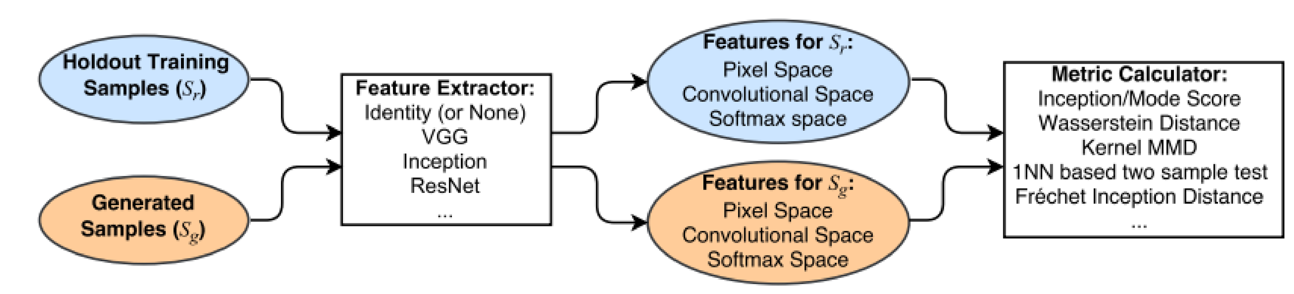


Fig. 5: Typical sample based GAN evaluation methods

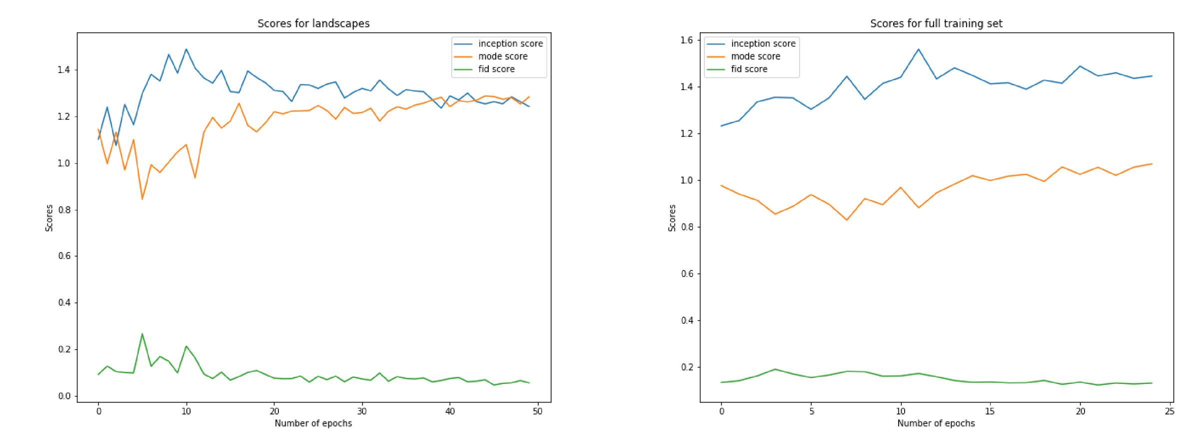


Fig. 6: Inception score, mode score, and FID score for landscapes and the entire dataset

## CONCLUSION AND FUTURE SCOPE

The results from the evaluation part has shown that how well the CNN's models are at classifying images, reaching accuray of around 85%, which is quite phenomenal.
The DC-GAN model has performed differently depending on which kind of paintings we want to generate. This demonstrates that the model does not generalize at all, and by contrast, performs very well in landscapes or portraits but not trying to learn an artist style for instance.
We see that the FID scores decreases with the number of epochs, as we know that lower FID scores mean better image quality and diversity. Thus, we can conclude that the GAN model has been able to generate better quality images as the number of epochs increase.
In future work, we would like to try other state-of-the art GANs models and evalaute the GAN by applying a classification task on the new generated images and identify which models are better depending on the type of the paintwork. We may also consider to augment the dataset to generate novel paintings based on artist's style.

## REFERENCES

[1] Kaiming He et al. "Deep Residual Learning for Image Recognition". In: *CoRR* abs/1512.03385 (2015). arXiv: 1512.03385. URL: http://arxiv.org/abs/1512.03385.

[2] Alec Radford et al. "UNSUPERVISED REPRESENTATION LEARNING WITH DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS". In: *CoRR* abs/1511.06434 (2016). arXiv: 1511.06434. URL: https://arxiv.org/pdf/1511.06434.pdf.

[3] Qiantong Xu et al. "An empirical study on evaluation metrics of generative adversarial networks". In: *CoRR* abs/1806.07755 (2018). arXiv: 1806.07755. URL: http://arxiv.org/abs/1806.07755.